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A fuel-efficient approach for platooning systems with ethical decision-making implications

Tiago Rocha Gonçalves*, Nelson de Moura*, and Fawzi Nashashibi

Abstract—Platooning system is a relevant solution for sustainable freight transportation due to its capability to substantially improve fuel efficiency, safety, and traffic flow. Most of the recent studies focus on the fuel-efficiency aspect while ignoring ethical aspects associated with the short inter-vehicle distance requirement. Unlike the literature, we address ethical implications that arise during platooning in addition to fuel-efficient improvement. We propose a decision-making algorithm based on a Markov Decision Process (MDP) that is able to switch between classical platooning controllers to improve fuel efficiency while accounting for a harm factor. Numerical results demonstrate the relevance of a joint design of ethical and fuel-efficiency aspects for suitable decision-making in platooning systems.

I. INTRODUCTION

A vehicle platoon is a particular arrangement by a group of coordinated autonomous vehicles (AV) able to keep short inter-vehicle distance, as shown in blue in Fig. 1. Some expected benefits of platooning systems include improved fuel efficiency, reduced traffic congestion, and increased safety for road users [1], [2], [3]. Each platoon member benefits, at different levels, from the air-drag resistance reduction due to the lowered pressure on the front of the follower vehicle. While platooning brings substantial fuel consumption advantages, on the other hand, such small distances raise a critical concern about public trust [4] in automated driving systems and ethical considerations [5] concerning their risk management capability. Unlike most existing works, we aim to precisely evaluate a trade-off between risk-taking and fuel-efficiency improvements in platooning systems.

It is well-known that the gains from platooning increase with the decrease of the distance between vehicles, so it is of interest to consistently keep the smallest distance between vehicles. However, the risk of collision increases with such a gap decrease. Assuming that today there is an imperative (economical and moral) urge to decrease carbon emissions, this article explores which gains can be obtained by decreasing the gap in a platoon, even if it means a determined increase in the collision risk. In this work, a such risk factor is considered in the main controller of the platoon, making the entire system more efficient while accounting continuously for possible collisions and their estimated severity. In our previous work [6], we proposed a Deep Reinforcement Learning (DRL) approach to dictate

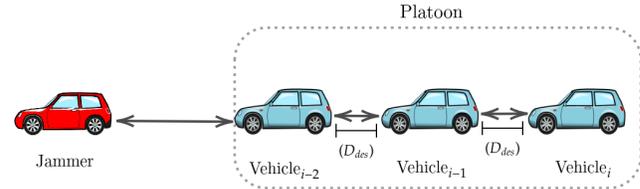


Fig. 1: Visualization of a three-vehicle platoon in blue. The vehicle in red is assumed to disturb the platoon’s performance.

the switching control rule in platoon systems. However, we did not cover ethical awareness, and only fuel-efficiency improvement was explored. To the best of our knowledge, no prior studies addressed the ethical decision-making for platooning systems with both harm and fuel efficiency contemplated in the objective function.

II. RELATED WORK

A. Ethics for AV

The highway environment is more predictable than the urban scenario since the number of possible interactions between users is smaller than in the urban context. Studies about ethical concerns are not as abundant for this reason, in comparison with dilemma decisions in urban areas where vehicles and vulnerable road users share the environment. But in the platooning case, a question about efficiency versus risk can be asked given the necessity to reduce carbon emissions and the central role that fossil-fuel combustion engines still play for mobility, which means that a strong reduction in a short amount of time is not expected. Granted, in the bigger scheme of things, such reductions are minimal but given the last reports from the IPCC [7], any possible avenue to reduce emissions must be explored without disregarding the safety concerns that may arise in the process. This is why such gains are counterbalanced here by an evaluation of the risk that it may bring to each vehicle in the platoon.

Note that platooning can be applied on buses, cars, and light-duty or heavy-duty trucks. The impact on fuel savings changes significantly according to the geometric shape of the vehicle, and the reader is referred to [8] for a detailed study on the drag coefficient reduction for car-like, truck, and bus platoons. However, in this work, when not stated otherwise, an N-vehicle platoon refers to N-cars platoon formation. The main reason is to keep consistency and simplify the analysis of ethical decision factors. The possible number of passengers, the velocity range of each potential vehicle,

*Denotes equal contribution

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the mass of the vehicle, and possible user-service provider responsibility concerns (for the bus case) can substantially alter the ethical evaluation.

Only a few works addressed ethical, moral, and legal responsibility for platooning systems. The authors in [9] proposed a meaningful human control (MHC) for a truck platoon that allows responsibility to be attributed and explained to each platoon member. More recently, the same authors extended their approach to cope with cooperative platoon systems in [10]. However, the aforementioned works simply provide guidance and recommendations, while in this work, we present mathematical models for the evaluation of platooning systems in terms of fuel efficiency and ethical AV decisions.

As for decision-making in dilemma situations, [11] proposes an approach based on mixed strategies to be conciliated using a Nash equilibrium approach. Basing the deliberation mechanics on Rawlsian contractualism, [12] proposes an algorithm to implement a max-min optimization similar to a Nash equilibrium but also adding a "veil of ignorance" to conceal information that might create a bias in the decision. Both are just theoretical propositions, without a physical implementation. In [13] a physical estimation of the collision risk with a barrier is done, so as to compare it with a possible pedestrian collision. Reasoning on the controller level, [14] coded different types of rules as ethical constraints for the trajectory control.

B. Platooning systems

Several approaches have already been explored to improve fuel efficiency for platooning systems. Consistently, most works have addressed the role of external forces such as aerodynamic drag, rolling resistance, and gravitation forces in the platoon, which are imperative to investigate the fuel consumption problem of platooning systems [15], [16], [6], [17], [8]. The authors in [15] conducted an experimental study to evaluate the impact of road topology on fuel reduction for platooning systems with an Adaptive Cruise Control (ACC) system. Unlike this work, they simply consider a fixed time-gap value per scenario evaluation regardless of the traffic condition. In contrast, we investigate the feasibility of actively switching two platooning controllers based on the traffic condition. The authors in [16] and [17] focused on the identification of when a platoon should be engaged and disengaged in a fuel-efficient manner, but without considering the impact of time-varying traffic conditions on the fuel efficiency and the harm factor in the platooning. In addition to energy-saving optimization, the work [8] proposes an analytical function that describes the relationship between the drag coefficient and the inter-vehicle distance gap beyond the measurement data range. Finally, our previous work [6] addressed the fuel consumption problem under stochastic disturbances through a reinforcement learning approach, while in this work, we adopt the value iteration framework to address both ethical considerations and fuel efficiency improvements for platooning systems.

III. SYSTEM MODEL

A. Platoon modeling under external forces

In this work, we consider a platoon system of size N consisting of one leader vehicle and $N - 1$ follower vehicles, as depicted in Fig. 1. It is well known that several external forces affect the vehicle's motion. Therefore, consider the following longitudinal vehicle model taking into account external forces that describe the dynamics for each vehicle i in this platoon:

$$\begin{aligned} m_i \cdot a_i(k) &= F_{eng_i} - F_{air_i} - F_{roll_i} - F_g \\ &= F_{eng_i} - \frac{1}{2} c_{D_i} \Psi_i(e_i(k)) A_{f_i} \rho_{air} v_i^2 - c_{r_i} g m_i \cos \theta - g m_i \sin \theta \end{aligned} \quad (1)$$

where the engine force is denoted by F_{eng} , the air drag force F_{air} , the roll resistance force F_{roll} , and the gravitational force F_g . Furthermore, $\{m, v, a\}$ designates the vehicle's mass, speed, and acceleration, respectively. c_D is the air drag coefficient, $\Psi(e) \in [0, 1]$ is the possible reduction air-drag for a given inter-vehicle spacing e , c_r is the roll resistance coefficient, A_f is the front area of vehicle, ρ_{air} is the air density, $\theta \in (-\frac{\pi}{2}, \frac{\pi}{2})$ denotes the road slope, and g is the gravitational constant. One key element of platooning is to lower the air-drag force by adjusting the inter-vehicle spacing, thus, improving fuel efficiency. Therefore, consider the following inter-vehicle spacing of the i th vehicle, in the discrete-time, given by

$$e_i(k) = p_i(k) - p_{i-1}(k) + l_{i-1} \quad (2)$$

and its difference as

$$\varepsilon_i(k) = v_i(k) - v_{i-1}(k) \quad (3)$$

where l_{i-1} is the length of the vehicle $i - 1$, and $p_i(k)$ and $v_i(k)$ are the front bumper position and velocity of the vehicle i , respectively. In practice, to simplify the design of the vehicle platoon control, the engine force is assumed to be able to counteract the air drag force, the roll resistance force, and the gravity force such that

$$\begin{aligned} F_{eng_i} &= u_i m_i + \frac{1}{2} c_{D_i} \Psi_i(e_i) A_{f_i} \rho_{air} v_i^2 \\ &\quad + c_{r_i} g m_i \cos \theta + g m_i \sin \theta \end{aligned} \quad (4)$$

where u_i is the platoon control input to be designed. Here, the engine force is used to linearize the dynamics by canceling the nonlinear terms. For convenience, we discretize the vehicle dynamics (1) under (4); to be more precise, we adopt the following model for the vehicle dynamics in the discrete-time form as in [18]:

$$\begin{bmatrix} p_i(k+1) \\ v_i(k+1) \\ a_i(k+1) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & T_s & 0 \\ 0 & 1 & T_s \\ 0 & 0 & 1 - \frac{T_s}{\tau_i} \end{bmatrix}}_{\hat{A}} \begin{bmatrix} p_i(k) \\ v_i(k) \\ a_i(k) \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ 0 \\ \frac{T_s}{\tau_i} \end{bmatrix}}_{\hat{B}} u_i(k) \quad (5)$$

where T_s is the sample-time, and τ_i is the time constant of the first-order low pass filter for each vehicle i . The idea is to approximate the dynamics of the throttle body and vehicle

inertia in order to avoid instantaneous response. Therefore, the open-loop model of the N-vehicle platoon system in the discrete-time form can be written as

$$x(k+1) = Ax(k) + Bu(k) + Ew(k) \quad (6)$$

where $x(k) := [p_j \ v_j \ 0 \ p_0 \ v_0 \ a_0 \ e_1 \ \varepsilon_1 \ a_1 \ \cdots \ e_{N-1} \ \varepsilon_{N-1} \ a_{N-1}]'$, indicates the state-space vector of the system, $u(k) := [u_0 \ \cdots \ u_{N-1}]'$, is the vector of all control inputs. Note that the state $x(k)$ contemplates the position and velocity of the obstructing vehicle, namely, the jammer, in addition to the whole platoon information. The assumption about the jammer's state is feasible since position and velocity can be measured/estimated via onboard sensors through the leader vehicle. $w(k) := [a_j^{\sigma(k)}(k)]'$ is the exogenous input, which is the acceleration of the jammer profile dictated by $\sigma(k)$ that is a random variable governed by a discrete-time Markov process and detail next.

Define $R = (r_{nm}) \in \mathbb{R}^{3(N+1) \times 3(N+1)}$, where $r_{nm} = -T_s$ for $n = 3i+2$ and $m = 3i$, $i = \{2, \dots, N\}$ and 0, otherwise. Now, take, $A = I_N \otimes \tilde{A} + R$, $B = [0_{3 \times 3} \ I_N \otimes \tilde{B}]'$, where \tilde{A} and \tilde{B} are defined in (5), \otimes denotes the Kronecker product, and I_N is the $N \times N$ identity matrix. Let

$$E = \begin{bmatrix} \begin{bmatrix} 0 \\ T_s \\ 0 \end{bmatrix} \\ 0_{(3N) \times 1} \end{bmatrix} \quad (7)$$

The state feedback control law $u(k)$ will be detailed next. We assume that the platoon behavior is affected only by the first vehicle in front of it, the jammer, which is a reasonable assumption for a longitudinal platoon. Thus, we assume a stochastic behavior of the jammer acceleration to disturb the platoon with two profiles. The first has zero acceleration, representing the platoon driving on a highway under light traffic conditions at a constant speed. The second is characterized by periodic braking and accelerating, so it models a heavy scenario of traffic conditions in terms of road safety as shown in [19]. Therefore, we are able to model the jammer dynamics as a stochastic system by adjusting its acceleration through the $\sigma(k)$ parameter as in (6). The reader is referred to Assumption 1 of [6] for additional details.

B. Fuel consumption model

Despite the presence of rolling resistance and gravitation forces, the aerodynamic drag force is definitely the most relevant in platooning systems. The main reason is that fuel efficiency changes significantly based on the total air drag force acting on the vehicles. Therefore, we next introduce a simple model that captures the intrinsic relation between consumed fuel and generated longitudinal force. Our discrete-time fuel consumed model is based on the energy loss model of Oguchi *et al.* [20]:

$$J(u) = \frac{1}{\rho_{prop} \cdot \eta_{eng}} \sum_{k=0}^{T_f} \zeta(k) (u_i(k) m_i + \frac{c_{D_i} \Psi_i(e_i) A_{f_i} \rho_{air}}{2} v_i(k)^2 + g m_i (c_{r_i} \cos \theta(k) + \sin \theta(k))) \cdot v_i(k) \cdot T_s \quad (8)$$

where

$$\zeta(k) = \begin{cases} 1 & \text{if } F_{eng_i}(k) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

indicates that propellant is used to power the vehicle i when $F_{eng_i}(k) > 0$. ρ_{prop} and η_{eng} are the energy density of the propellant in $[J/L]$ and the constant efficiency of the engine, respectively. Unlike our previous work [6], we adopt the polynomial-based model of [8] that captures the impact of the vehicle intra-platoon position and distance gap for light duty vehicle, i.e., dictates the function $\psi_i(\cdot)$ for a car-platoon.

C. Control systems for platooning

1) *Adaptive Cruise Control*: The ACC controller is one of the precursors of Advanced Driving Assistant Systems (ADAS) that can significantly improve driving safety. It is regularly adopted in platooning systems due to its string stability capabilities for a constant time-gap policy [21]. Furthermore, the ACC controller does not require any type of communication between platoon members. The controller can be written as a state feedback control law given by:

$$u(k) = -K_0 x(k) \quad (10)$$

where $K_0 \in \mathbb{R}^{N \times 3(N+1)}$ is the controller ACC gain defined by

$$K_0 = \begin{bmatrix} \chi_i & \zeta_i & 0 & \cdots & 0 \\ 0 & \vartheta_i & \zeta_{i+1} & 0 & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & \vartheta_i & \cdots & \vartheta_i & \zeta_{N-1} \end{bmatrix} \quad (11)$$

where

$$\chi_i = \begin{bmatrix} -\frac{\lambda_i}{h_i} & -\frac{1}{h_i} & 0 \end{bmatrix}, \quad (12)$$

$$\zeta_i = \begin{bmatrix} \frac{\lambda_i}{h_i} & \frac{1+h_i \lambda_i}{h_i} & 0 \end{bmatrix}, \quad (13)$$

$$\vartheta_i = \begin{bmatrix} 0 & \lambda & 0 \end{bmatrix}, \quad (14)$$

are the ACC controller gain with a constant time-gap spacing policy proposed by [22], and h and λ are the time-gap and design gain parameters, respectively, for all $i = \{0, 1, \dots, N-1\}$.

2) *Cooperative Adaptive Cruise Control*: Unlike the previous controller, CACC is highly dependent on the intended acceleration of the previous vehicle u_{i-1} , which requires network communication and, for that reason, is subject to packet delay and loss. To simplify, we adopt the one-vehicle look-ahead communication topology without any information from the leader. Therefore, we assume perfect communication only between consecutive vehicles. The CACC controller is written as state feedback control given by:

$$u(k) = -K_1 x(k) \quad (15)$$

where $K_1 \in \mathbb{R}^{N \times 3(N+1)}$ is the CACC gain defined by

$$K_1 = \begin{bmatrix} \chi_0 & \zeta_0 & 0 & \cdots & 0 \\ 0 & \xi & \varphi_i & 0 & \vdots \\ 0 & 0 & \xi & \varphi_{i+1} & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots \\ 0 & 0 & \cdots & \xi & \varphi_{N-1} \end{bmatrix} \quad (16)$$

where the first term is the ACC controller previously implemented in the leader vehicle to be in conformity with spacing policies imposed by public entities. The next term is then,

$$\varphi_i = \begin{bmatrix} k_{p,i} & k_{d,i} & 0 \end{bmatrix}, \quad (17)$$

$$\xi = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}, \quad (18)$$

for all $i = \{1, \dots, N-1\}$, which are the CACC controller gains based on the sliding-surface controller introduced by [21] but with $c_i = 0$ (parameter responsible for weighting the leader message) that yields

$$k_{d,i} = 2\rho_i\omega_i \quad (19)$$

$$k_{p,i} = \omega_i^2 \quad (20)$$

where ρ_i , and ω_i , are the controller damping ratio and bandwidth for the vehicle i , respectively.

Note that we adopted the enhanced controlled proposed by [6] to smooth the unsuitable transient responses. The reader is referred to the aforementioned work for further details.

IV. MDP DEFINITION AND APPLICATION

The longitudinal behavior of the platoon is formulated as a Markov decision process (MDP) [23] to find an optimal control usage policy while contemplating ethical factors. Such a mathematical framework is defined by the tuple (S, A, p, r, γ) , where S and A are the state and action space, respectively. After taking action $a \in A$ in state $s \in S$, the agent reaches state $s' \in S$. The transition is given by $p(s'|s, a)$, which characterizes the dynamics of the system, while the reward obtained from it is equal to $r(s, a, s')$; $\gamma \in [0, 1]$ is the discount factor, that controls the importance of future rewards on the decisions taken in the present. The choice of an MDP to model the platoon control is adequate because it deals with two main quantities, fuel efficiency and risk, which are both intrinsically connected to the gap distance between vehicles, i.e. a single objective optimization is enough in this scenario.

A. State space and action

The state transition is obtained propagating the initial state using all the available actions for the defined number of transitions n_t , being composed of the same elements defined by $x(k)$ at equation (6). The actions themselves are composed of which controller is being used by the platoon, the ACC introduced in subsection III-C.1 or the CACC in subsection III-C.2, and the assumed obstructing vehicle acceleration, mode 0 or 1, represented in figure 2 (more details about this assumption will be given later on); hence, the total number of actions being considered is given by $N_{act} = N_{plat} \cdot N_{jam}$ where N_{plat} is the number of switching controllers and N_{jam} is the number of jammer modes. Each controller was chosen to deal accordingly with each possible mode, which represents a particular behavior from the obstructing vehicle; the more complex the behavior is represented, the more controllers may be necessary to obtain an optimal performance. To find each possible state that needs to be considered in an iteration, the transition is executed using a tenth of the real time-step for the transition t_t . For example, if $t_t = 20s$ then the

next state is calculated applying the action ten times for two seconds each.

B. Transition probability

Considering that the obstructing vehicle used here (implemented as in [6]) has only two different acceleration profiles, the transition probability uses two Gaussians to estimate the period in which each mode is used, as seen in figure 2. It is considered that after one mode the obs. vehicle passes to the other and then restarts the process. The necessary parameters, (μ, σ) , are obtained offline from an estimation based on a previously generated set of jammer profiles. All jammer's velocity and acceleration profiles are generated based on the algorithm displayed in 1.

Algorithm 1: Jammer profile generation

```

1 mode = 0;
2  $t_m = e^{\lambda_{mode}}$ ;
3 for  $t_m$  do
4   | Generate_Point(mode)
5 end
6 mode = (mode + 1)/2

```

Always starting from mode 0, which is characterized by a constant velocity for the jammer, the amount of time in each mode is calculated by an exponential function modulated by two constants (20 for mode 0 and 30 for mode 1). The function *Generate_Point* creates the next point based on the previous one and on the current mode. For mode 0, the absolute value of acceleration is equal to $0.4854m/s^2$ until the jammer's velocity reaches $80km/h$, then the acceleration is set to zero until the transition time finishes. Mode 1 oscillates the velocity between $80km/h$ and $30km/h$ using an acceleration of $0.4854m/s^2$ and a deceleration of $-2.94m/s^2$ (figure 5) with equal duration, similar to [6].

With these jammer samples (30 were used), two Gaussians are fitted, one for each mode, according to the amount of time for each mode counted in each sample. The counting of each time period is done with an inverse classification, from array to mode, is done using two logistic functions and the jammer acceleration array; $f(a) = \frac{1}{1+e^{-50(x-0.4)}}$ defines the mode for positive acceleration values and $f(a) = 1 - \frac{1}{1+e^{-50(x+0.4)}}$ for negative ones.

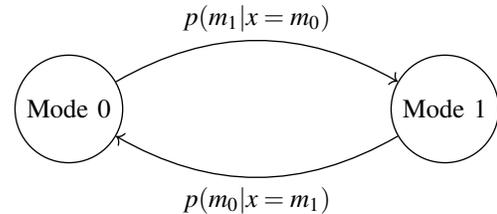


Fig. 2: Acceleration modes and their transition for the obstructing vehicle.

Finally, the transition probability is then calculated using the cumulative density function (cdf) from each Gaussian

according to the mode being considered by the action. For example, if the current mode observed is 0 (this is known given that the behavior of the obstructing vehicle is observed at the policy calculation), then $p_{\text{trans}} = p(t_{m_0} > t_{\text{curr}} + t_{\text{trans}})$ is the probability calculated to assume that the mode continues at 0; this probability is calculated using the survival function (1-cdf) minus also the cdf until 0, since the period for a mode cannot be smaller than zero. To rectify the removal of negative values, both are normalized to one.

C. Reward

The reward, represented by equation (21), is composed by two parts: a score for the fuel consumption that depends on the amount spent during the transition; and a score concerning the current risk for each vehicle on the platoon, given the velocity and the proximity of each member.

$$r(s_t, a_t, s_{t+1}) = s_{\text{fuel}} + s_{\text{risk}} \quad (21)$$

1) *Fuel consumption*: The fuel consumed during the transitions is calculated as proposed in [6], represented in equation (8), but with a drag coefficient based on the results published in [8] and displayed in figure 3. From the aforementioned work, the coefficients for car-like drag were used in the fuel consumption estimation.

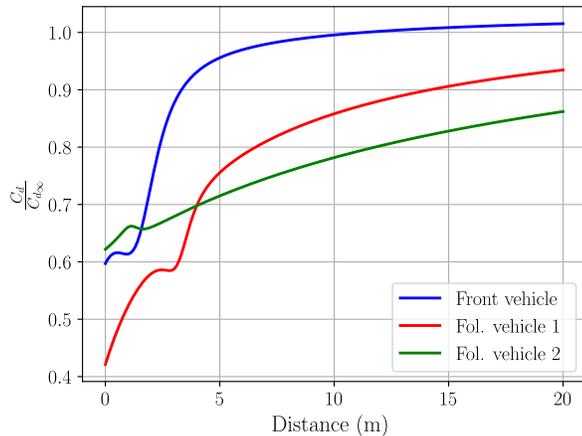


Fig. 3: Drag equations made available in [8]

The fuel consumption score is calculated according to (22), which is similar to (8) but without the constant to transform the energy from joules to liters of fuel and to account the engine efficiency.

$$s_{\text{fuel}} = w_{\text{fuel}} \cdot \sum_{k=0}^{T_f} \zeta(k) \left(u_i(k) m_i + \frac{c_{D_i} \Psi_i(e_i) A_{f_i} \rho_{\text{air}}}{2} v_i(k)^2 + g m_i (c_{r_i} \cos \theta(k) + \sin \theta(k)) \right) \cdot v_i(k) \cdot T_s \quad (22)$$

2) *Risk*: This term is inspired in the work published in [5], where a property called harm was proposed to measure the severity of a hypothetical collision. In simple terms, the reward is calculated by equation 23, considering that h_i represents the harm for the platoon member i .

$$s_{\text{risk}} = w_{\text{risk}} \cdot \sum_{N_{\text{veh}}} h_i(s_i, a_i) \quad (23)$$

Each vehicle is actually exposed to different risks in the platoon: the front vehicle can hit the obstructing vehicle or be hit by the vehicle behind, while the last follower can only hit the previous follower. All these cases are quantified by equation 24, considering the current velocity difference between vehicles and the constant of vulnerability, which scales the difference of velocity during the collision with the probability of a MAIS3+ (maximum abbreviated injury scale above 3, [24]) injury. The variable Δv_i^c is the difference of velocities for the same vehicle before and after a collision considering the conservation of the linear moment, as defined in [5].

$$h_i(s_i, a_i) = [w_{\text{fr}} \quad w_{\text{re}} \quad w_{\text{vel}}] \cdot \begin{bmatrix} c_{\text{vul}}^{\text{fr}}(i, i-1) \cdot \Delta v_i^c \\ c_{\text{vul}}^{\text{re}}(i, i+1) \cdot \Delta v_i^c \\ c_{\text{vul}}^{\text{vel}}(i, i) \cdot v_i \end{bmatrix} \quad (24)$$

For the evaluation of the vulnerability constant, the results made available in [25] for rear and front collisions are used directly as $c_{\text{vul}}^{\text{fr}}$. Both curves follow a logistic form with y-axis midpoint at 44.5 and 52.5 km/h, respectively. The Δv used to calculate the vulnerability constant is actually the difference of initial velocities for both vehicles in question, not as defined for the harm calculation. The last term of equation 24, $c_{\text{vul}}^{\text{vel}}(i, i)$, represents the risk of having a high velocity and was described by using the same logistic representation for the rear collision but using directly the velocity, not the Δv . This quantity has as sole function to serve as a cost for high velocities, given that both rear and frontal collision only accounts for the difference of the velocities. The adopted weights $\{w_{\text{fr}}, w_{\text{re}}, w_{\text{vel}}\}$ from equation 24 were equal to $[1, 1, 0.1]$, respectively.

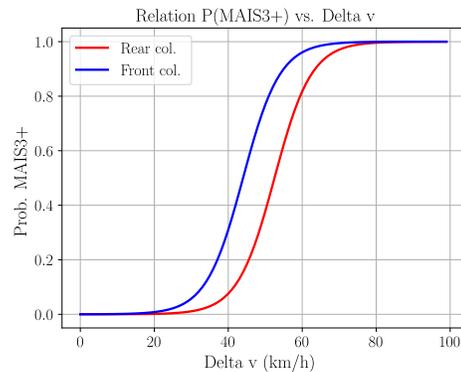


Fig. 4: Probability of a MAIS3+ injury per Δv from [25]

It is important to consider that the use of such data may not be exact for the current scenario (highway environment).

The data used to calculate such curves comes from urban accidents, which have a smaller range of velocities (from 0 to 50 km/h), different in comparison with a highway environment that can reach 120 km/h in some countries. However, due to the extreme lack of public available data of accidents that have an AIS (abbreviated injury scale) injury measure indexed [26], the data approximated by figure 4 will be used.

D. Policy calculation

The optimal policy is calculated using the value iteration algorithm similar to [5]. It uses the principle of dynamic programming to find the optimal average return from a given state

$$V_{t+1}(s_t) = \max_{a \in A} \left[R(s_t, a_t, s_{t+1}) + \gamma \cdot \sum_{s_{t+1}} P(s_{t+1}|s_t, a) V_t(s_{t+1}) \right] \quad (25)$$

In particular, the most appropriate controller/policy is extracted by using equation 26 after solving the Bellman equations.

$$\pi^*(s_t) = \operatorname{argmax}_{a \in A} \sum_{s_{t+1} \in S} P(s_{t+1}|s_t, a_t) V_t(s_{t+1}) \quad (26)$$

V. EXPERIMENTAL RESULTS

In this section, we introduce the adopted simulation environment and numerical results that demonstrate the relevance of a joint design of ethical and fuel-efficiency aspects for suitable decision-making in platooning systems. We adopted the python-based longitudinal platoon simulator proposed by [6] to handle the longitudinal dynamics, the fuel consumption, and the stochastic behavior of the jammer. In addition to it, we implemented a risk prediction system and a Value Iteration algorithm to compute the optimal policy for a given MDP.

A. Setup

In this work, we considered a homogeneous platoon of size $N = 3$ and with actuator lag of $\tau_i = 0.2 \text{ s} \quad \forall i \in \{0, \dots, N-1\}$. Our platoon system is assumed to drive on a highway scenario with stochastic disturbances, as previously described. The corresponding controller and MDP parameters in our simulation are shown in Table I. Some other parameters used to model external forces are $\rho_{air} = 1.225 \text{ kg/m}^3$, $c_r = 0.008$, and $\theta = 0^\circ$.

B. Results

In order to show the benefits of the proposed framework, we used the threshold logic method proposed by [6] for comparisons. More precisely, we adopt the optimized threshold control version to allow fair comparisons since the naive approach does not properly tune the threshold parameter. Figure 5 displays the velocity profile of the jammer vehicle used per episode during simulations. Note that due to limited space, we omit the jammer profile of episodes 3 and 4. Table II shows the experimental results on average of our approach against the threshold logic method proposed by [6]. As can be seen, our approach outperforms the compared

TABLE I: Control and MDP simulation parameters

| Control and Traffic | | MDP | |
|-------------------------------|------------|------------------------------|-------------|
| Parameter | Value | Parameter | Value |
| Simulation duration | 3000 s | Discount factor (γ) | 0.95 |
| Jammer profile | Stochastic | Sampling time (δ) | 100 s |
| Platoon size (N) | 3 | Fuel weight (w_{fuel}) | -1 |
| ACC | | Risk weight (w_{risk}) | [1, 1, 0.1] |
| Time-gap (h) | 1.4 | | |
| Gain (λ) | 0.5 | Vehicle | |
| Standstill dist. (d_{ss}) | 4 m | Mass (m) | 1200 kg |
| CACC | | Air-drag (C_D) | 0.6 |
| Leader factor (C) | 0 | Front area (A_f) | 2.1 m |
| Desired dist. (d_{des}) | 5 m | Actuator lag (τ) | 0.2 s |
| Damping ratio (ξ) | 2 | | |
| Bandwidth (ω_n) | 0.5 Hz | | |

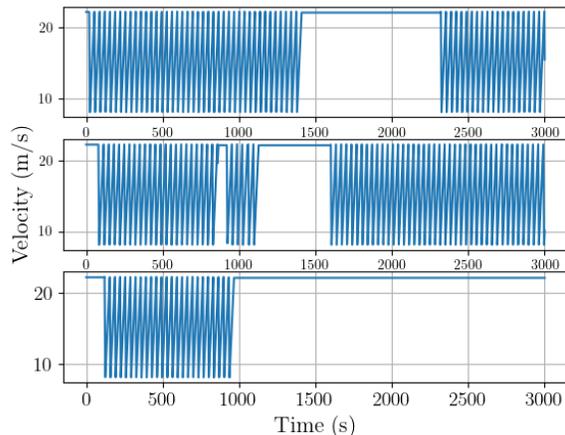


Fig. 5: Velocity profile of three stochastic jammers (zero, one, and two).

framework since lower fuel consumption is obtained for the same disturbance. The main reason is that we implemented a simple prediction behavior of the jammer that allows a more suitable policy to be used while accounting for the harm factor as modeled in the risk-reward as in equation 24.

TABLE II: Average platoon performance comparison in terms of fuel consumption percentage (lower is better).

| Episodes | Threshold optimized [6] | Ours |
|----------|-------------------------|---------|
| Jammer 0 | 100 % | 99.36 % |
| Jammer 1 | 100 % | 98.64 % |
| Jammer 2 | 100 % | 93.29 % |
| Jammer 3 | 100 % | 97.81 % |
| Jammer 4 | 100 % | 99.16 % |

Another aspect that explains why the gain in fuel savings was not bigger is that this comparison focuses on the moment that the controller is switched due to a different behavior from the jammer. First, there are not that many transition modes in the jammer's profiles used (only two considered); and second, the changes are rather extreme, which does not allow the algorithm to take advantage from the risk estimation to remain for more time in the CACC controller. And lastly, it is well known that platooning gains using car-

like vehicles are rather weak since the gains that can be obtained by drag reduction only happen with small distances, differently from trucks, for example.

VI. CONCLUSION

We present a novel approach that encompasses both fuel-efficient and ethical implications in the decision-making for platooning systems. In addition to considering platooning systems under stochastic traffic conditions, we account for the notion of risk modeled by the harm parameter and included it in the decision-making system. Preliminary results show the potential of our approach for improving fuel efficiency while accounting for a harm factor. This work paves the way toward a joint design of ethical and fuel-efficiency aspects for suitable decision-making in platooning systems. In terms of future work, we aim to adopt selected datasets with realistic velocity profiles of vehicles to improve the disturbance model.

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